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Abstract

Immigrants are traditionally seen as hard to survey. Their number is often too small to be analysed via data gained in general population surveys, and registers to identify them are often missing or incomplete. Therefore, researchers are forced to use alternatives for sampling. In the case of the Austrian Immigrant Survey 2016, an onomastic (name-based) approach was used, establishing a sampling frame in a two-step procedure. This article describes the concept and the implementation of the sampling and evaluates the sample that could be realised.

Keywords

hard to reach populations, immigrants, Onomastic sampling, probability samples, sampling frame

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Introduction – The Onomastic Approach

Names are distinct markers for geographical and cultural origins; therefore, they are of significance not only for the named individuals themselves but are also a precious source for the social sciences. Linguistic areas shape specific names, and this fact may be used to identify members of specific populations as well (Mazières & Roth, 2018). Therefore, it comes as no surprise that sampling techniques using an onomastic – name-based – approach have gained some prominence in the social scientific repertoire. Lists including names, such as phonebooks or population registers, can be used to select specific-sounding names to establish analytical and sampling frames. As literature shows, these approaches have been successfully applied to not only migration studies (Reichel & Morales, 2017; Schnell et al., 2013), but also a wide range of other research topics, such as population composition (Mateos, 2014), social mobility in the historical context (Clark, 2014) or even big data-based approaches to estimate diversity within social groups (Mazières & Roth, 2018).

One of the main advantages of using onomastic approaches for survey research is the fact that they allow one to draw a random sample as long as a comprehensive list of names can be accessed (Fernandez et al., 2006). However, there is still no consensus whether it is an adequate strategy when it comes to building representative survey samples for specific populations such as immigrants (Fernandez et al., 2006; Font & Méndes, 2013; Sproston & Mindell, 2006). The main problems and concerns are that names are highly sensitive culturally and are tied to specific ethnicities only with a certain probability (Mazières & Roth, 2018), but not in an absolute way. Linguistic variations and related families of languages make it difficult to assign names clearly to a specific ethnic or immigrant group. Furthermore, some members of a target group – especially married women – are less likely to be covered by a sampling frame built when using surnames, while using a frame built up on given names faces the problem that they may also be commonly used outside a specific community (Mazières & Roth, 2018). Thus, onomastic classification often requires specific context information, such as geographical, cultural and language-based secondary sources (NamSor, 2014, 2).

Grounded on this current understanding of the advantages and challenges of onomastic-based methods, the following article describes the approach used for the Austrian Immigrant Survey 2016 (AIS2016) and explores problems regarding representativity arising from general or specific characteristics of the approach chosen. Firstly, we will discuss the reasons for using an approach that includes an onomastic component in the sampling procedure (section 2), followed by a description of our approach and the challenges associated with it (sections 3 and 4). A description of the actual sample and its evaluation follow (section 5) and, finally, a discussion closes the paper (section 6).

Reasons for Designing the Austrian Immigrant Survey 2016

Increasing global mobility, the ongoing debate on how immigrants influence their host societies and – last but not least – the latest wave of refugees from the Middle East has led to a growing demand for data on immigrant groups (Getmansky et al., 2018; Pötzschke & Braun, 2017, 634; Verwiebe et al., 2018a, 229). This is particularly the case in the European Union, but it also exists beyond these countries where the discourse on migration and integration has become a priority in the public and political spheres (Reichel & Morales, 2017, 1). In this regard, a Eurobarometer survey from late 2017 reveals that only a third of the participants feel well-informed about immigrants (Eurobarometer, 2018a, 8).

However, this demand for data and information goes way beyond the recent waves of refugees (UNECE, 2015). Immigrants are a fundamental force shaping post-industrial societies (Verwiebe et al., 2018a, 229), and they have been an essential part of the post-WWII history in many central European countries, such as Germany and Austria (Fassmann et al., 1997).

Thus, it is understandable that the demand for data is strong in Austria. Researchers recently emphasised that there are no actual large-scale studies on immigrants, especially regarding their economic situation (Reinprecht & Latcheva, 2016; Weichselbaumer, 2017). Publications that actually use empirical data also highlight this deficit and, therefore, restrict themselves to specific regions, such as Vienna, the capital of Austria (Berghammer & Fliegenschnee, 2014), use experimental study designs and qualitative set-ups (Ahn, 2018; Berghammer & Fliegenschnee, 2014; Weichselbaumer, 2017) or use micro census data (Grandner & Gstach, 2015), which is limited to specific socio-structural variables. Due to the salience of the issue, the Social Survey Austria 2016 (SSA2016) research team decided to carry out a separate Austrian Immigrant Survey (AIS).

However, no matter how one defines immigrants, they have proved to be populations which are *hard to survey* (Tourangeau, 2014; Vargas-Silva, 2012). In most cases, traditional full probability random samples – the gold standard for survey research – are either cost-prohibitive or even impossible to carry out (Font & Méndes, 2013, 22) for the following reasons:

1. *Immigrants are too small a group to be analysed within general population surveys:* only 7 % of the population in the European Union can be classified as foreign citizens and approximately half of them hold citizenship of another EU country (Eurostat, 2015, 3). Hence, immigrants are a rare population in most countries. Consequently, it is not possible to survey different ethnicities, religions or even nationalities within a general population survey as their share in the population (and hence in the sample) is too small (Beauchemin & González-Ferrer, 2011, 105).
2. *Appropriate sampling frames for specific immigrant surveys are often not available:* population register-based sampling would be the superior strategy whenever possible (Andreß & Careja, 2018, 5), but register data often do not contain the information required, as foreign citizenship is too narrow a definition of migration background for sociological purposes. Furthermore, registers may not be available or are incomplete (Beauchemin et al., 2016; Landry & Shen, 2005; Reichel & Morales, 2016, 5; Salentin & Schmeets, 2017, 12).
3. *In many cases, immigrants are vulnerable groups:* several reasons may exist for this, ranging from precarious legal status to cultural issues or language skills (Antoni, 2011, 3; Deding et al., 2008, 105). Consequently, the risk of unit non-response is higher than for other parts of the population (Fawcett & Arnold, 1987).

All three points are true for Austria and the Immigrant Survey 2016. Although Austria has a large number foreign citizens residing in the country compared to other EU countries (see Table 1), specific groups of immigrants – no matter how one defines the status of immigrant – are too small to be analysed within data from general population surveys. Even if immigrants from several countries of the same region are combined, as it is often done with people from the states that previously made up Yugoslavia, the group is still not expansive enough. In the case of countries from former Yugoslavia just stated, they do not represent more than 5 % of the population, despite of being the largest group of non-German-speaking immigrants in Austria.

Table 1 – Foreign Citizens in Austria; 2018 (Source: Statistik Austria, 2018a; Data retrieved via STATcube)

Citizenship	Number	% Among Individuals with Non-Austrian Citizenship	% of the Austrian Population (N = 8,822,267)
Germany	186,841	13	2.1

Serbia	120,174	9	1.4
Turkey	117,297	8	1.3
Romania	102,270	7	1.2
Bosnia / Herzegovina	95,189	7	1.1
Hungary	77,113	6	0.9
Croatia	76,682	5	0.9
Poland	62,190	4	0.7
Syria	48,103	3	0.5
Afghanistan	45,724	3	0.5

Furthermore, some methodical problems must be assumed. Following the numbers provided by Statistik Austria (2018a), the samples of the European Social Survey (ESS7) (2015) and SSA2016, each containing about 2,000 individuals, should have yielded 120 cases with roots in former Yugoslavia, meaning that either the survey individuals themselves or at least one of their parents comes from that region. In reality, they only accounted for 67 and 93 individuals, respectively, going back to an under-coverage (Beauchemin & González-Ferrer, 2011, 105) or non-response of immigrants. Under-representation of immigrants or people with a migration background can often be observed in Austrian social surveys.

In addition, the AIS was supposed to follow another perspective. Firstly, acknowledging the fact that Austria has a long tradition of migration and integration, the researchers involved in the AIS2016 decided to forfeit the common definition of "migration background", which argues that only people who are themselves born outside of Austria or have both parents born outside of Austria are immigrants (Statistik Austria, 2017; UNECE, 2015, 136). This definition may be acknowledged internationally, however, publications highlight that this definition does not cover families that include Austrian citizens and partners from foreign states (Reinprecht & Latcheva, 2016); a fact of uttermost importance when discussing immigration-related issues in Austria, as the country has been significantly influenced by several waves of "guest workers" (*Gastarbeiter*) (Rathkolb, 2015). These workers came to Austria during the last half of the 20th century and stayed, not only creating their own distinct communities but also integrating into broader society (Fassmann et al., 1997; Rathkolb, 2015; Reinprecht & Latcheva, 2016).

Therefore, the researchers saw the need to use a broader approach to define both immigrants and the necessary background information of "migration background" for the project. The deciding was made to define immigrants as individuals who have a "migration background", meaning that either the individual in question or one of his or her parents has to be born abroad. With this broader definition of "migration background", it becomes possible to include children resulting from intermarriages between citizens and immigrants. The latter is a group of great importance and has been the subject of much discussion both in the international (e.g. see Schuck, 2018, for the US context) and national context of Austria (Scheibelhofer, 2018; Verwiebe et al., 2018b). However, as expected, this theory-based choice had far-reaching methodological implications. It could no longer be used as a sampling frame because the population register does not capture the birthplace of parents.

As to vulnerability, Austria can be seen as traditionally immigrant sceptic (Rathkolb, 2015). Recent studies have shown that the diction used in Austrian policy-related discussions is highly stigmatizing (Fuchs et al., 2016), while Moser et al. (2016) showed that immigrants have a high risk of being early school leavers. Taking these considerations, restrictions and a limited budget into account, the study design was fixed as follows:

- The survey should capture Austria's two most relevant non-native German-speaking immigrant groups, which are people with Turkish or former Yugoslavian backgrounds.
- The target population was defined as people living in Austria, 16 years or older, with either themselves or at least one of their parents born in one of the countries named. This definition is broader than the international definition used by the UNECE (2015, 136), which identifies migrants only when both parents were born outside the country of residence. This broader definition was chosen because it was an explicit aim of the study to find out whether different cultural backgrounds have an influence on the attitudes and opinions of the immigrants and their offspring (e.g. whether children of immigrants and children of mixed couples are different).
- The sample should be representative of the target population. The Austrian micro census was available as a reference, at least in terms of age, sex and education, to check for this.
- The sample should be probability-based to be in line with other academic or official surveys.
- The interviews should be carried out by telephone, mainly for costs reasons. Native speakers were hired as interviewers to avoid non-response caused by language problems.

Options for a Sampling Frame – and Potential Sources of Errors

The Austrian micro census is a household survey with a rotating panel design and a sample size of about 45,000 individuals in each round. As it is part of official statistics, participation is mandatory and provides the best population estimates available on a national level.[i] However, it delivers neither information on attitudes nor values of the survey population. Nor does it contain enough information to build a sampling frame or do substantial analysis. As the AIS2016 intended it to be comparable to a number of surveys targeting exclusively immigrants (e.g. Beauchemin et al., 2016; Crul et al., 2012; Ersanilli & Koopmans, 2011; Morales & Giugni, 2011; Recchi & Favell, 2009), it was clear that the study would need to find a solution for an appropriate sampling frame. At least the raw data of the micro census could be used as a reference to evaluate how specific criteria, for example, age, sex and education, match the corresponding populations.

There are generally different sampling options for an immigrant survey (see Table 2), but none of them is without problems (e.g. Font & Mendez, 2013).

Table 2 – Different sampling methods for immigrant studies

Approach	Sampling Frame	Pros	Cons
Quota sampling	Unclear/not defined	Sample composition matches population when it comes to the controlled variables chosen Low costs	No probability sampling Unable to estimate potential bias when it comes to all other variables
Snowball sampling	Ethnic networks (e.g. cultural associations)	Low costs	No probability sampling Restricted to people

			active in such networks
Respondent-driven sampling (Salganik & Heckathorne, 2004)	Ethnic networks (e.g. cultural associations)	Information on networks allows for calculation of selection probabilities (in contrast to snowball sampling)	Dependent on a fully networked community Hard to apply on spread out populations Unclear whether correct estimates can be realised in practice
Centre sampling (Baio et al., 2011)	Areas highly frequented by people with a specific marker (e.g. religion)	Provides access to hidden or invisible communities	Information about a number of aggregation centres that are regularly visited by the immigrants has to be known
Household sample	List of households	Frame available; allows for probability-based sampling	Low chance of reaching households with immigrants; extensive screening procedure
Population register	List of individuals registered	Frame available; allows for probability-based sampling	Only information about individuals but not their parents, thus, only possible for first-generation immigrants
Random digit dialling	Phone Numbers*	Frame available; allows for probability-based sampling	Low chance of reaching individuals from specific immigrant groups; extensive screening procedure
Random route	List of eligible streets	Frame available; allows for probability-based sampling	Low chance for reaching households with immigrants; extensive screening procedure
Onomastic Sampling	Population register and list of eligible names (e.g. phonebook)	Specific frame available; allows for probability-based sampling	Only individuals that feature traditional names become part of the sampling frame

* At least the structure of how phone numbers are built in the country has to be known.

Quota sampling was excluded from the start, as a probability-based approach was considered to be of high importance, the same was true for the use of ethnic networks for snowball sampling (including variations, e.g. respondent-driven sampling) and location-based sampling (e.g. centre sampling). These approaches would have been problematic, as the used definition for the target population included people who are not part of the traditional immigrant communities, which these sampling procedures are better suited for. Furthermore, an address-based random sampling procedure had to be ruled out, because of the small population sizes and the low probabilities of drawing an address that matches the target population. Additionally, previous experiences with the ESS7 and SSA2016, which both use address-based random sampling, showed under-coverage problems when it came to immigrant groups.

The same problem would be expected using the population register. This would not only have needed special governmental permission, leading to a several months delay in the research process, but bore the risk that permission may have been denied. Additionally, the register only contains information on citizenship and country of origin of the respective individuals, but not of their parents, which would have been necessary for the definition of migration background applied. Thus, individuals whose parents moved to Austria from abroad – commonly called second-generation immigrants – could not be identified. Consequently, this approach was ruled out.

In some cases, random digit dialling and random route-based approaches are presented as alternatives (Reichel & Morales, 2017), but they would also have needed thorough and extensive screening procedures and increased the cost of the fieldwork tremendously.

Consequently, the decision was made to use an onomastic approach to build a sampling frame. While the method can be applied to any data source that includes names – such as the population register – the survey decided on the telephone register for the following reasons: as already stated, there are legal barriers to access the official population register and whether we would obtain permission was unclear. In addition, the interviews were to be made by telephone (mainly for costs reasons) and the register does not include telephone numbers. As an alternative, the IFES (Institute for Empirical Social Studies) field agency contracted provided access to the Austrian telephone register, which includes every telephone number registered – landline and cellular – and the full names of the individuals who registered the phones. This register is compiled by the Austrian postal and telecommunication service – Telekom Austrian Group – and, according to information provided by IFES, it covers approximately 42 % of Austrian residents age 15 and older. Thus, this list is far more comprehensive than any public telephone book available and allows one to complete a computer-assisted telephone survey.

The register opened up the chance to cut down the number of entries via an onomastic approach to two lists that only included individuals with names that matched common names of the aforementioned countries of origin. The Turkish and west Slavic languages (Bosnian, Serbian and Croatian) yield specific names (or variations of names) distinctive from other language families. This would allow a random selection of participants and screening expenditure would be much lower. As past research had shown that onomastic approaches are useful to identify individuals of Turkish origins, it was expected that the method would be applicable (Bouwhuis & Moll, 2003). Native language interviewers were hired to help individuals facing language barriers to access easily and reduce unit and item non-response. This was also an advantage of the computer-assisted telephone interviews, as it was easier to use native speakers compared to a face-to-face study.

However, there were several methodological and theoretical challenges that had to be addressed. Firstly, the problem of coverage is still an issue when using the telephone register as a sampling frame. Not everyone owns a phone; some individuals might register more than one number, and some will not register their phones themselves, for example, a father who registers mobile phones for his children, or someone who rents a flat will register the landline for the whole family (Reichel & Morales, 2017). As mentioned previously, IFES states that the register covers 42 % – which is around 3.1 million individuals – of Austrian residents age 15 or older, however, the register incudes approximately five million telephone numbers.

Salentin (1999) and Fernandez et al. (2006) flagged this previously as a potential risk for German studies on immigrants, but available data on phone penetration in the country lead to the assumption that this kind of error should be neglected (Statistik Austria, 2018b[ii]).

Nevertheless, it should be noted that the telephone register has been a partial 'black box' for the researchers involved. The field agency was only allowed (or willing) to provide information on the key features of the list but did not open the list to the researchers.

Secondly, the onomastic-based selection of names was not without its own problems either. While names may be typical for a specific linguistic, cultural and ethnic group, they are, of course, not perfectly and exclusively tied to it. In other words, there is only a probability of identifying an individual from a specific origin and the probability threshold when to include a name on the list had to be decided (Mazières & Roth, 2018). Thus, the individuals identified may not be part of the immigrant population that is the target of the research. As mentioned previously, this was compensated for via additional screening questions prior to the actual data collection. Furthermore, current literature shows that there is still some discussion whether onomastic screening works better with given names compared to surnames (Salentin, 2007; Mazières & Roth, 2018). Salentin (2007, 42) illustrated that surnames yield a higher chance of identifying immigrants, as they are less subject to naming trends. Moreover, he expanded on this, explaining that certain groups of immigrants are more likely to adjust given names and family names (Salentin, 2014, 40). However, other researchers argue that given names are better suited (Mazières & Roth, 2018). This is based on the argument that using given names increases the chance to include women, who are more likely to change their surnames when marrying, individuals who are born outside families consisting exclusively of members of the targeted immigrant groups, and individuals who came from other backgrounds (Mazières & Roth, 2018, 6). This would not have been possible if surnames had been used. Given names seemed to be advantageous as the project tried to use a broader understanding of the migration background than commonly used.

The so-called dictionary method (cf. Humpert & Schneiderheinze, 2002) was used for our sampling frame: a list of names established by the linguistic department of the University of Vienna including probability scores calculated based on their relative frequencies for names that are also used in other than one of the target populations. It was decided to use given names with a high probability (> 80 %) to match the target populations. When applying this on the phone register mentioned previously, approximately 32,000 individuals (not phone numbers!) with Turkish roots could be identified by IFES. This group featured close to 900 different given names, counting small variations and adaptions as well. The micro census for 2016 estimates the Turkish population in Austria that matches the defined population of 209,902 individuals (also see Table 5). Thus, the list covered approximately 15 % of the population in which the researchers were interested.

The IFES provided the following numbers for the former Yugoslavian subsample: approximately 100,600 individuals identified, featuring around 1,800 different given names, including variations. Once again using the micro census for 2016 to estimate the former Yugoslavian population matching the description used, it should consists of 481,412 individuals (also see Table 6). Thus, the final list to draw the sample included approximately 21 % of the population in which the researchers were interested.

Yet, the approach resulted in the situation that only individuals with names or variations of names that can be matched with a certain language could be identified. Consequently, individuals from former Yugoslavia could be included in the sampling frame only if they stem from Bosnia, Serbia or Croatia, as these languages derive from the same western Slavic linguistic background (Sussex & Cubberley, 2006). As the Slovenian and Macedonian languages are different (ibid.), these names were captured to a much lesser extent. Consequently, immigrants with roots in today's Slovenia and Macedonia, which were also part of former Yugoslavia, are underrepresented in the final sample. There are further sources of under-coverage: as only names associated with a certain region and specific probability scores were used, individuals with less traditional names would not be included.

Table 3 gives an overview of the associated advantages and disadvantages.

Table 3 – Identified advantages and disadvantages of the two-step sampling frame used

Advantages	Disadvantages
Random selection: a clearly defined list makes random drawing possible.	Coverage error 1: accuracy of the telephone register is unclear ('black box').
Screening for over-coverage: the share of individuals who are not part of the target population is low, allowing for an effective screening at the beginning of the interview.	Coverage error 2: linguistic families do not necessarily meet target group definitions.
Reaching vulnerable group members: using native speakers as interviewers lowers access burdens.	Coverage error 3: specific given names are used in specific ethnic groups – but not only and not exclusively.

Establishing the Sample

Fieldwork for the project started in September 2016 and in addition to answering the questionnaire, meta-information on the interview process was collected. The sample size was targeted at 300 completed interviews for each group of inhabitants with either a Turkish or former Yugoslavian migration background. Regarding the total of 600 interviews, the field agency contacted 4,633 numbers, with 2,095 tied to Turkish names and 2,538 tied to names coming from west Slavic languages belonging to the Bosnian, Serbian and Croatian language family. According to the agreement with the field agency, each number had to be called up to three times, on varying weekdays and at varying hours. If the person targeted was not available, the responding person was asked to state a better time to contact the individual in question. When looking at the detailed breakdown responsible for this high number of contacts (see Table 4), some striking features can be observed.

Table 4 – Drawing the sample – from total contacts to the final sample

	Turkey		Former Yugoslavia		Total	
	N. Obs	%	N. Obs	%	N. Obs	%
Total Contacts	2,095	100	2,538	100	4,633	100
Neutral non-response/non-Contact						
Technical error (wrong number, etc.)	452	21.6	497	19.6	949	20.5

Commercial phone number	48	2.0	42	1.7	90	1.9
Not part of target population (via screening question)	283	13.5	301	11.9	584	12.6
Base for response rate	1,312	62.6	1,698	66.9	3,010	65.0
Adjusted gross sample	1,312	100	1,698	100	3,010	100
Non-neutral non-response						
Interview refusal	483	36.8	546	32.2	1,029	34.2
Interview break-off	34	2.6	63	3.7	97	3.2
No contact possible (no one answered the phone)	283	21.6	447	26.3	730	24.3
Target person not available	212	16.2	342	20.1	554	18.4
Final number of interviews	300	22.9	300	17.7	600	19.9

Firstly, the fact that each subsample had more than 20 % of non-contacts due to technical errors, such as non-existent numbers, which may be interpreted as an accuracy problem of the telephone register. As this is the official register provided by the Austrian postal and telecommunication service, it also shows that such sources should not be used uncritically. Another 11.9 %, respectively 13.5 %, of all telephone numbers contacted turned out to not to belong to the target group, meaning that the onomastic method discarding inapplicable names can be evaluated as being effective in both languages. Furthermore, it is consistent with Liebau et al. (2018, 21), who argued that onomastic sampling for Germany may be more likely to miss a migration background than wrongly classify someone without a migration background.

Of course, this says nothing about the number of applicable names having been removed from the list.

The adjusted gross sample is n = 1,312 for people with a Turkish and n = 1,698 for those with a former Yugoslavian migration background. Non-contact rates resulting from an inadequate sampling frame are high but not outside the numbers usually reported for telephone interviews (Busse & Fuchs, 2012; Fowler et al., 2016; Groves et al., 2009).

The same is true when looking at the adjusted gross sample: one out of five calls resulted in a completed interview. The main reasons for this moderate success rate were that either nobody picked up the phone or the target person was not available for an interview. Among the Turkish contacts, this amounted to 38 %, while for the former Yugoslavian contacts, it comprised 46 % of the draws. As we do not have any additional information on the specific reasons, this kind of non-response is classified as non-neutral, although it might also be neutral non-response to some extent.

Regarding interview refusal, approximately a third of the potential interviewees in both groups declined to give an interview. The number of interviews that were only partially completed were low – between 2.6 and 3.7 % of the interviews were terminated early by the interviewees.

The overall response rate was better among the Turkish (23 %) than among the immigrants from former Yugoslavia (18 %). Nevertheless, both groups were far below the reported response rates that the face-to-face interviews of the Social Survey Austria 2016 (53 %; cf.

Prandner, 2019, 519) and the ESS7 (approx. 50 %; cf. Beullens et al., 2017, 5) have yielded in recent years. However, the numbers are in line with other incentiveless telephone surveys on populations which were not hard to research (Mercer et al., 2015).

As mentioned above, respondents were offered the chance to do the interview in their first language, deploying native speakers as interviewers. Strikingly, nearly half of the successful interviews with Turkish immigrants were completed in the Turkish language (n = 141), while only one of six were done in either Bosnian, Serbian or Croatian (n = 47). Whatever conclusion one may draw, this fact highlights the need to offer multi-language survey designs when covering immigrant populations.

Evaluating the Composition of the Sample

The central question is whether the coverage and non-response problems reported affected the composition of the final sample. This can be evaluated by comparing some key demographic variables with the numbers provided in the micro census datasets available. We will focus particularly on age, gender, education, region of residence and citizenship.

Table 5 – Austrian Citizenship: Turkish AIS 2016 sample compared to the micro census 2016

	Percentage that acquired or was born with Austrian citizenship		
Generation	AIS 2016	Micro census (Age 16+)	Diff.
1st Gen. (n = 218/n = 148,938)	51.40	46.60	+4.80
2nd Gen. (n = 78/n = 60,964)	73.10	77.30	-4.20

Table 6 – Austrian Citizenship: former Yugoslavian AIS 2016 sample compared to the micro census 2016

	Percentage that acquired or was born with Austrian citizenship		
Generation	AIS 2016	Micro census (Age 16+)	Diff.
1st Gen. (n = 215/n = 395,229)	57.00	33.10	+24.10
2nd Gen. (n = 58/n = 86,183)	75.90	66.10	+9.80

Applying the definition used in the Austrian Immigrant Survey on micro census data – the raw data of the micro census 2016 was acquired to calculate comparable numbers between the AIS and the micro census directly – shows that 46.6 % of Turkish first-generation and 77.3 % of second-generation immigrants hold Austrian citizenship (see Table 5 for details). The survey data collected meets these values roughly, but the difference for immigrants from former Yugoslavian is much higher: among first-generation immigrants, 57.2 % claim to be Austrians by citizenship. According to the micro census, this is true only for a third of this group. The sample also overestimated the rate of citizenship for second-generation immigrants from former Yugoslavia, but not as high (see Table 6 for details). The causes for these and all deviations reported in the following may stem from coverage problems and non-response or measurement issues. Unfortunately, a more specific classification is not possible without further information.

Another large difference can be identified for the Turkish immigrants when the sample is compared regarding the size of their current hometowns. While the micro census data states that approximately four out of ten Turkish immigrants live in Vienna, only a quarter of the survey sample lives in the Austrian capital (see Table 7 for details). The estimates for immigrants from former Yugoslavia are somehow better in this respect, but still not good (see Table 8).

Table 7 – Size of current hometown: Turkish AIS 2016 sample compared to the micro census 2016

Size of city	AIS 2016 (%)	Micro census (Age 16+; %)	Diff. (%)
Pop. < 100,000	53.70	50.00	+3.70
Pop. 100,000 + (excl. Vienna)	21.10	11.20	+9.90
Vienna	25.20	38.80	-13.60
Adjusted gross sample (n/N)	294	209,904	

Table 8 – Size of current hometown: former Yugoslavian AIS 2016 sample compared to the micro census 2016

Size of city	AIS 2016 (%)	Micro census (Age 16+; %)	Diff. (%)
Pop. < 100,000	51.60	46.20	+5.40
Pop. 100,000 + (excl. Vienna)	15.10	12.70	+2.40
Vienna	33.30	41.10	-7.80
Adjusted gross sample (n/N)	273	481,411	

More mismatches become evident when moving forward to the classical demographic characteristics – age, sex and education. While the gender balance is only off by a few percentage points, age and educational level show larger differences even at a univariate level. Individuals under 45 are underrepresented among the migrants from former Yugoslavia (-12 %), as are those who only completed compulsory education (-18.5 %). The same is true for Turkish immigrants. According to the micro census, 61 % of the latter group had only completed the mandatory compulsory education, while this group is only 31 % in the sample (see Tables 11 and 12 in the appendix for details on this).

Those mismatches are even higher when combining variables and building subgroups (see Table 9 and 10). Education is generally highly overestimated in the sample: 34.40 % of the respondents with Turkish and 36.30 % with former Yugoslavian roots claim to have completed secondary education ("Matura"), while only 9.20 %, respectively 18.00 %, claim this according to the micro census 2016. Within these groups, one can observe severe effects for Turkish immigrants, especially when it comes to young men under the age of 25. This category is 31 % points off the reference values. Among the women, all categories are 28 to 39 % points off in relation to the micro census, except for those under the age of 25 who are only 13 % points off.

The sample of people coming from the countries of former Yugoslavian shows similar problems, but not as extreme. According to the sample, men under 25 are only slightly (+4.20 %) more highly educated than their reference category and younger women in the sample are much more likely to have completed a higher education level (+26.40 %). However, the mismatch is much higher for men in all other age brackets. This is especially evident regarding the elderly men (age 65+) who participated in the survey. They are much more likely to have completed secondary education ("Matura") than the reference category in the micro census (+32.10 %).

It becomes obvious when looking at these results that the secondary goal of the AIS2016 was not completed. Both samples drawn show severe differences to the micro census data.

Table 9 – Turkish AIS 2016 sample compared to the micro census 2016; criteria chosen for representation

	Percentage that completed secondary education ("Matura")		
Men			
Age bracket	AIS 2016	Micro census (Age 16+)	Diff.
16-24	38.90	7.92	+30.98
25-44	34.80	14.11	+20.69
45-64	22.90	9.39	+13.51
65+	23.10	12.60	+10.48
Women			
Age bracket	AIS 2016	Micro census (Age 16+)	Diff.
16-24	27.80	15.09	+12.71
25-44	52.50	13.58	+38.92
45-64	40.20	5.47	+34.73
65+	30.00	1.59	+28.41
n/N	294	209,904	

Table 10 – Former Yugoslavian AIS 2016 sample compared to the micro census 2016; criteria chosen for representation

	Percentage that completed secondary education ("Matura")		
Men			
Age bracket (n/N)	AIS 2016	Micro census (Age 16+)	Diff.

16-24	25.00	20.80	+4.20
25-44	37.50	20.60	+16.90
45-64	28.60	17.10	+11.50
65+	44.40	12.30	+32.10
Women			
Age bracket (n/N)	AIS 2016	Micro census (Age 16+)	Diff.
16-24	52.00	25.60	+26.40
25-44	35.30	27.10	+8.20
45-64	25.70	18.70	+7.00
65+	0.00	7.40	-7.40
n/N	285	481,411	

Conclusion/Discussion

Was the onomastic method, which enabled the research of the AIS2016 to draw a random sample, a success when it came to representing the target populations? Regarding the tables and results presented above, one might be tempted to say: “No”. The method applied did not provide a representative sample for the immigrant populations researched. The data does not match the results from the micro census even on a univariate level and is even worse when cross-tabulating information.

Nevertheless, such a conclusion might be too hasty. Unfortunately, we do not have enough information about the specific sources of error which led to the bias we finally had to state in our sample, but at least our experiences give us some hints regarding what could be changed in the future.

The main problem was not only the often-stated lack of an appropriate sampling frame (Groenewold & Lessard-Phillips, 2012; Reichel & Morales, 2017), but also the fact that the study aimed to cover the whole of Austria, which has a very uneven distribution of immigrants. The insistence of using a probability-based selection mechanism led to the decision to use an onomastic approach. This is not unique for the AIS2016 or even Austria, as some other researchers (e.g. Fernandez et al., 2006; Font & Méndes, 2013; Sproston & Mindell, 2006) came to similar conclusions. The main argument is that the usage of an onomastic approach may offer pragmatic advantages when it comes to cost and organisation of a study, but, in the end, this approach fails to provide a solution to the problem of the missing sampling frame.

However, there were not many alternatives, as argued above. Non-probability samples, such as quota samples, would have faced the same problem in the end, as either a list of potential respondents is needed to select from or one has to rely on ethnical networks, such as cultural associations, on personal acquaintances of native interviewers or on social media networks. Those may have had the potential to improve data quality but resulted in limitations regarding the scope of the study (e.g. only particular regions, cities or subpopulations), as those methods work best in smaller projects (Andreß & Careja, 2018, 14; Baio et al., 2011). When checking for some demographic features, such an approach may lead to a representative sample regarding the quota variables applied but has a high risk of bias when it comes to political opinions or attitudes towards integration, which are usually of central interest in such surveys.

Taking the outcome of the AIS2016 into account makes further reflection necessary. Our starting point was the telephone register and the weaknesses of it were mentioned above. However, the register was provided by the same source – the Austrian postal and telecommunication service – as the one used for the general population sample of the SSA. The latter one produced fairly good results (Prandner, 2019). The alternative would have been the official population register. This had to be ruled out for this specific study because of the high administrative barriers in Austria. While it would provide a list of all individuals officially registered in the country and, thus, provide a better basis for the application of the onomastic method, Austria is one of the numerous countries in Europe where a nation-wide register-based probability samples is not feasible (Andreß & Careja, 2018, 15).

Additionally, the given name-based selection of individuals used was certainly responsible for some coverage error and, according to current literature, this is substantial (Fernandez et al., 2006; Salentin, 2014). While over-coverage seemed to be moderate in our sample (about 20 % in both languages) and easy to detect and remove by screening, we have little information on the amount and the effect of under-coverage. This was also in accordance with the findings of Liebau et al. (2018) reported for Germany.

However, future research should consider that a combined approach may be helpful to identify some of the bias (Bouwhuis & Moll, 2003); especially as there are limited clues that under-coverage may have caused bias: are given names in Austria associated with education or citizenship? Salentin (2014, 40) argues for Germany that a correlation between socio-structural integration, education and religiosity exists, while Gerhards and Hans (2009) demonstrated that immigrants from the Mediterranean region are more likely to use assimilated given names. The results of the AIS2016 imply that these potential explanations need be researched for Austria as well, to gain a deeper and better understanding of how immigrant communities are set up.

Following the Total Survey Error perspective, non-response would be a second source or error impairing representation. Again, the information we have is not sufficient for detailed analyses; the rate of refusals is high but not outstanding compared with other surveys. Unfortunately, the reasons for refusal are unknown as are the causes of non-contacts. At least it is plausible that bias may stem from this step of the sampling process, as better-educated immigrants and people holding citizenship are more likely to participate in a survey dealing with immigration and integration issues. This is so especially if one considers the general immigrant sceptic climate in Austria and the public discussion on immigrants – in particular refugees – at that time. The same is true for measurement issues, which can also be responsible for bias. Respondents might have had the feeling that education and citizenship are desirable things – at least from the perspective of the host society. This would match established notations found in methods literature (e.g. Gabler & Hoffmeyer-Zlotnik, 1997; Häder, 2010).

Finally, there is another point that may be taken away by the reader. The project generated a large amount of data and the sample sizes are large enough for substantial multivariate analysis. The effects reported via those methods are, in most cases, size-sensitive and, thus, the argument could be made that those are independent from representation criteria (e.g. Bacher & Prandner, 2018). Therefore, the sample provides very much needed and valid data for many research applications that go beyond simple descriptions of distribution.

Appendix

Table 11 – Age and Sex – Distribution (%)

	Turkey	Former Yugoslavia

Age bracket	AIS 2016	Micro census (Age 16+)	Diff.	AIS 2016	Micro census (Age 16+)	Diff.
16-24	15.30	19.80	– 4.50	13.20	14.50	– 1.30
25-44	50.30	48.10	+ 2.20	31.10	43.20	– 12.10
45-64	31.00	27.60	+ 3.40	45.10	32.50	+12.60
65+	3.40	4.40	-1.00	10.60	9.80	+ 0.80
Sex	AIS 2016	Micro census (Age 16+)	Diff.	AIS 2016	Micro census (Age 16+)	Diff.
Male	56.10	52.40	+ 3.70	44.00	49.20	– 5.20
Female	43.90	47.60	– 3.70	56.00	50.80	+ 5.20
n/N	294	209,902		273	481,412	

Table 12 – Highest Education Completed – Distribution (%)

	Turkey			Former Yugoslavia		
Education	AIS 2016	Micro census (Age 16+)	Diff.	AIS 2016	Micro census (Age 16+)	Diff.
Compulsory Sch.	31.00	60.90	– 29.90	17.90	36.40	– 18.50
Voc. Training	34.70	26.80	+ 7.90	46.50	40.90	+ 5.60
Secondary Ed.	24.50	8.90	+ 15.60	21.60	16.20	+ 5.40
Tertiary Ed.	9.90	3.40	+ 6.50	13.90	6.40	+ 7.50
valid n/N	294	209,902		273	481,412	

[i] http://statistik.at/web_de/statistiken/menschen_und_gesellschaft/soziales/ausstattung_privater_haushalte/021850.html

[ii] http://statistik.at/web_de/frageboegen/private_haushalte/mikrozensus/index.html

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